MOODY'S ANALYTICS

MODELING METHODOLOGY
MAY 2012

Authors
Danielle H. Ferry
Tony Hughes
Min Ding

Contact Us
Americas
+1.212.553.1658
clientservices@moodys.com

Europe
+44.20.7772.5454
clientservices.emea@moodys.com

Asia (Excluding Japan)
+85 2 2916 1121
clientservices.asia@moodys.co

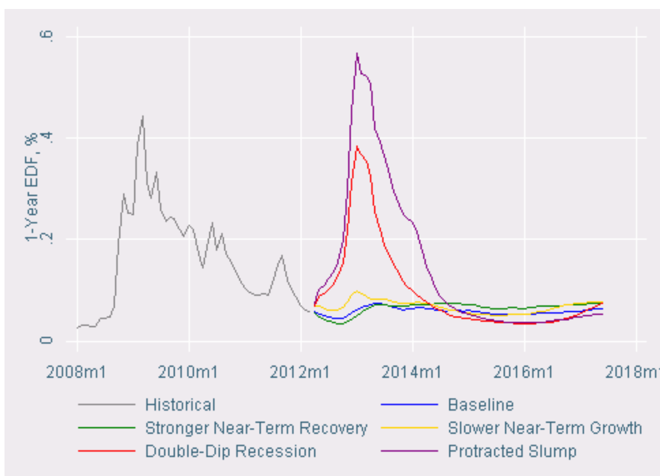
Japan
+81 3 5408 4100
clientservices.japan@moodys.com

Stressed EDF™ Credit Measures for North America

Summary

Stressed EDF™ (Expected Default Frequency) credit measures are one-year, firm-level default probabilities conditioned on a range of macroeconomic scenarios. Stressed EDF measures can substitute seamlessly for traditional EDF measures whenever it is necessary to assess credit risk in alternative macroeconomic situations. Two examples of such applications are Basel II/III capital and loan loss provision calculations. Stressed EDF measures bring together macroeconomic scenarios from Moody's Analytics' economic forecasting unit and the public firm EDF model, the industry-leading structural credit risk model for default probability. Our unique approach affords users a rigorous means to evaluate the impact of plausible macro-financial events on credit risk at both the firm and portfolio level. Stressed EDF metrics – for a baseline, one upside, and three downside economic scenarios – are available at a monthly frequency, over a five-year forecast horizon, and are updated each month. For US firms, we also provide Stressed EDF scenarios derived from the Federal Reserve baseline and supervisory stress economic scenarios. This paper describes the modeling methodology employed in the North America module of Stressed EDF measures.[1]

Exhibit 1: Stressed EDF Scenarios for Honeywell International, Inc.



[1] The North America module includes firms incorporated in the US, Canada, and the Caribbean islands.

Table of Contents

1 Introduction

Recent events – from the collapse of Lehman Brothers to the European sovereign debt crisis – have shown the importance of regular and robust stress testing for prudent risk management. Generically, stress testing means assessing financial vulnerability to extreme events. Macro stress testing, which has been the preferred approach among high-profile central banks and regulators, more precisely means analyzing financial risk under plausible, adverse macroeconomic conditions.[2] The joint World Bank and IMF Financial Sector Assessment Program (FSAP), begun in 1999, was an early innovator in this regard. In response to the 2008 financial crisis, the Federal Reserve Bank and European Banking Authority introduced an ongoing series of bank stress tests that explicitly require assessments of financial risk to be conditioned on macroeconomic scenarios. The Basel Accords, too, increasingly advocate the need for incorporating economic assumptions in stress tests of capital adequacy. In developing Stressed EDF measures, Moody's Analytics has adopted the approach taken by regulators and other supervisory authorities. That is, Stressed EDF metrics are designed to facilitate the exercise of projecting best estimates of an entity's financial health under future, adverse macroeconomic conditions and comparing these to a baseline scenario.

Identifying appropriate scenarios is of utmost importance in stress testing.[3] In related research, macro stress tests are typically designed around stressing a single economic driver (i.e., a 10% oil shock). Some allow for that shock to impact the other systemic drivers – although this usually limits the number of drivers included to just a handful – while others improbably treat the economic variables as exogenous to one another.[4] Another approach, the results of which are often difficult to interpret for a lay audience, involves generating economic stress scenarios by taking random draws from Monte Carlo simulations of the macro drivers.[5]

Stressed EDF measures are one-year, default probabilities (PDs) conditioned on holistic economic scenarios developed in a large-scale, structural macroeconometric model framework. This framework ensures that the macro drivers are internally consistent (i.e., the unemployment rate rises when GDP falls), and although it does not explicitly allow for feedback effects from Stressed EDF measures to the macroeconomy, the inclusion of credit spreads in the macro model assumes implicit feedback effects.[6] Plausibility is a key condition for useful stress scenarios and a key feature of Moody's Analytics' macroeconomic scenarios. Consequently, Stressed EDF measures are intuitive, context-driven, and realistic measures of credit risk, making them accessible to audiences beyond credit risk managers.

Because they are derived from the Moody's Analytics public firm EDF model, Stressed EDF measures can substitute seamlessly for traditional EDF metrics whenever it is necessary to assess credit risk in alternative, future macroeconomic conditions. Applications are not limited to financial stress testing exercises on metrics such as regulatory and economic capital, however. Stressed EDF scenarios can be useful for credit officers, underwriters, portfolio managers, and others in assessing counterparty risk, particularly when operating in cyclically sensitive industries or when expanding business lines to unfamiliar geographic regions. Additionally, users requiring projections of credit risk may focus exclusively on the baseline or may construct a weighted average (or expected value) series.

Stressed EDF metrics are firm-level measures. "What if" analysis using Stressed EDF measures, whether done at the firm or portfolio level, will therefore explicitly account for idiosyncratic default behavior and, in the latter case, portfolio composition. They are available on a monthly frequency, extending five years into the future, for a baseline, one upside, and three downside economic scenarios. For US-based firms Moody's Analytics also provides Stressed EDF metrics based on the Federal Reserve's baseline and supervisory stress economic scenarios developed for the Comprehensive Capital Analysis and Review (CCAR).[7] Monthly updates in Stressed EDF measures reflect changes in the macroeconomic scenarios and, due to the dynamic panel nature

[2] Foglia (2009) provides an overview of the macro stress testing methods employed by selected supervisory authorities.

[3] Breuer and Krenn (2000) discuss some of these challenges.

[4] Asberg (2008) and Pesaran et al (2005) model the impact of the shock on other systematic drivers in a vector autoregression framework. In Bunn et al (2005), the shock permeates into other aspects of the economy via a structural macro model. Boss (2002) and Virolainen (2004) forecast each macro variable, independently, using AR(2) processes.

[5] An example of this approach can be found in Drehmann (2005).

[6] Feedback effects between financial markets and the real economy are well-documented, but difficult to model. See, for example, Balke (1995) and Jacobson et al (2005).

[7] The current CCAR economic scenarios were designed in November 2011. Stressed EDF measures based on revised CCAR scenarios can be expected to be available within two weeks of the public announcement of the next CCAR round's scenarios.

of the model, changes in each entity's recent credit risk history. The North America module of Stressed EDF measures includes over 85 percent of the North American firms in the public firm EDF universe.[8]

In this paper, we describe the modeling methodology Moody's Analytics employs to generate Stressed EDF measures for North American firms. This work builds upon earlier efforts by Hughes et al.[9] The methodology can be best described as a macroeconomic-based approach to projecting default probabilities which are themselves the product of an asset value model that utilizes equity market information and financial statement data.[10] In the next section we describe the primary Stressed EDF inputs and discuss briefly the models used to produce them. Section 3 describes the Stressed EDF methodology itself. In Section 4 we discuss validation of the specifications and follow that up with some examples and applications of Stressed EDF measures at the single-name and portfolio level in Section 5. Section 6 discusses an enhancement, Stressed EDF measures based on user-defined macroeconomic scenarios, and Section 7 concludes.

2 Stressed EDF Model Inputs

The Stressed EDF methodology can be divided into two distinct steps – an estimation step and a projection step. In the estimation step, we ran regression analyses on fixed samples of historical data to yield estimates of the model parameters linking credit risk to macroeconomic drivers. To this end, we constructed a panel dataset containing firm-level EDF records and historical macroeconomic factors over time. Whenever possible, firms were matched with the macroeconomic data corresponding to their country of incorporation.[11] The historical economic data are "second party" – that is, they are sourced directly (i.e., from the US Bureau of Labor Statistics) but obtained through Moody's Analytics' Economic & Consumer Credit Analytics (ECCA) database. The firm-level records are from Moody's Analytics' proprietary EDF database, which includes data from company financial statements and equity markets in addition to Moody's Analytics' calculated EDF-related metrics. In the projection step, we apply the estimated model parameters to ECCA's economic scenario forecasts to produce Stressed EDF measures. The next two sections briefly describe the methodology used to generate Moody's Analytics' EDF metrics and Moody's Analytics' ECCA economic scenario forecasts.

2.1 Public Firm EDF Model Review

Stressed EDF metrics are conditional, one-year, point-in-time EDF measures. That is, they represent the probability a firm will default within one year, as of some point in the future, conditional on a set of assumptions about the macroeconomy. As such, it is important for Stressed EDF users to understand the basic methodology of the Moody's Analytics public firm EDF model and the EDF measure itself.

The Moody's Analytics public firm EDF model belongs to a class of quantitative PD models referred to as structural or asset value models. The model is based on the pioneering work of Black and Scholes (1973) and Merton (1974), collectively referred to as BSM. In this section we sketch out the basic mechanics of the public firm EDF model. We necessarily omit many details of the model's theoretical underpinning and practical implementation.[12]

---

[8] The public firm EDF module for North America includes about 6000 publicly listed firms incorporated in the US, Canada, and the Caribbean islands. The reason Stressed EDF model coverage is less than 100% of this is a direct result of the methodology and is explained in greater detail in Section 3.1.

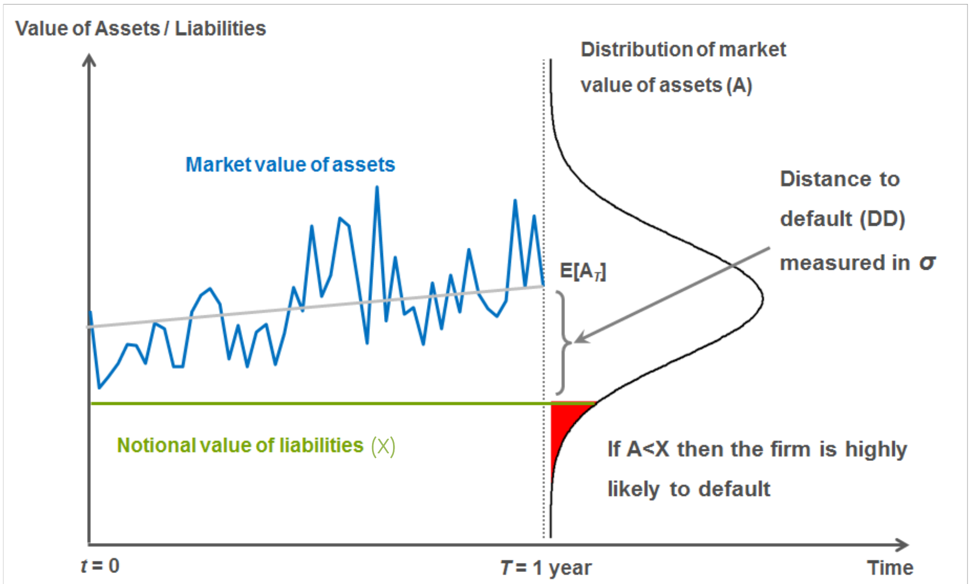
[9] Hughes and Liu (2011) and Hughes et al (2007).

[10] See Chan-Lau (2006) for a description and examples of the different types of models used to estimate default probabilities.

[11] Matching is constrained both by the availability of a consistent set of historical macroeconomic variables and the availability of scenario forecasts for the economic variables included in the models. In the North America module, Canadian firms are matched with Canadian macroeconomic data and all other firms are matched with US macroeconomic data. Exceptions include corporate profit growth, the Baa spread, and the Ted spread, which are available only for the US.

[12] Crosbie and Bohn (2003) and Dwyer and Qu (2007) discuss many theoretical and practical aspects of the public firm EDF model in great detail.

Exhibit 2: Default Process in the Basic BSM Model



The basic presumption of asset value models is that there is a causal, economically motivated reason that default occurs. Exhibit 2 illustrates the mechanics of the default process in a basic BSM-type structural model. Looking ahead in time, say one year (T=1), default is highly likely to occur when the market value of the firm, shown by the blue line, is insufficient to cover its liabilities due on or before time T (the green line) – i.e. firms tend to default when they are insolvent. This follows from the fact that equity holders are residual claimants on the value of the firm. If the market value of the firm is negative, equity holders can and will "put" the residual value of the firm to creditors. The probability of default is, therefore, the likelihood that the asset value of the firm (A_T) is less than the liabilities due at time T, which we call the default point (denoted by X).

The graph illustrates that a firm's default risk is determined by the shape of its asset value (including both equity and debt values) distribution at the horizon date, as well as the position of the distribution in relation to the liabilities due at the horizon date. The above economic intuition can be translated into three quantifiable variables: the expected value of a firm's assets, E(A_T), the volatility of its asset distribution, σ, and the level of its default point, X. The interaction of the three variables is encapsulated by the firm's distance-to-default (DD), which under some largely innocuous assumptions about the firm's asset value evolution, can be expressed as:

$$DD \approx \frac{\ln(A) - \ln(X)}{\sigma} \qquad (1)$$

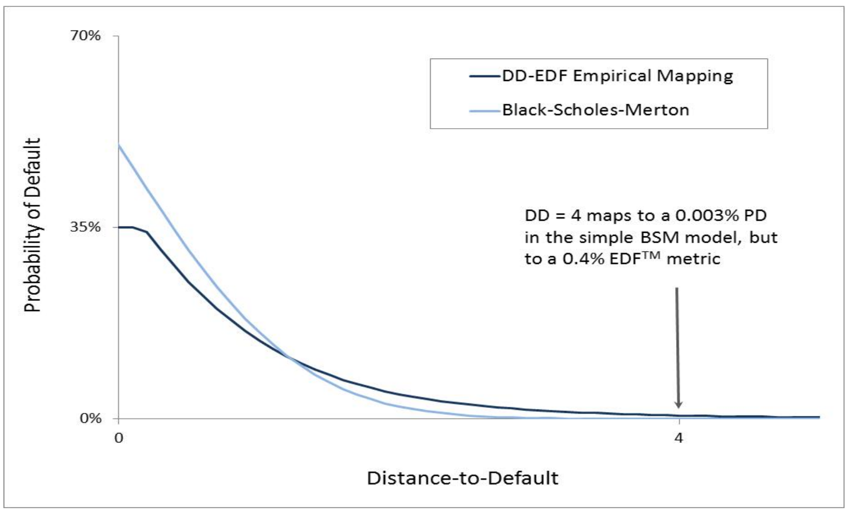
where A denotes the current market value of assets.

This simple equation states that a firm's relative credit risk (measured by DD) is a function of its financial risk and its business risk, two factors that are core concepts of fundamental credit analysis. The numerator of Equation (1) is market leverage – i.e. financial risk. All else equal, higher leverage reduces DD and increases the probability of default. The denominator of Equation (1) is business risk. Firms in industries with high asset volatility tend to exhibit higher risk of default, all else equal. For example, technology companies have higher asset volatility than utilities, and the former tend to default more often than the latter. DD is the number of standard deviations a firm's expected asset value is away from the default point. It provides a rank ordering of firm default risk. A firm with a DD of, say 4, is less likely to default than a firm with a DD of 3.

In order to derive probabilities of default useful for credit risk management, DDs must be mapped to PDs. In the simple BSM model, this probability may be easily calculated from the cumulative normal distribution. Indeed, in Exhibit 2 it is exactly equal to the red shaded area. However, default probabilities calculated analytically from the normal distribution tend to underestimate default risk, with the magnitude of the understatement growing larger as the PD gets smaller. This is because the tails of the normal density are too thin relative to the actual density of default probabilities. To put it simply, defaults of medium and high quality firms have occurred more often than what the normal density would suggest. Because of this fact, Moody's Analytics' public firm EDF model has been calibrated to yield default probability levels that closely match observed historical default rates. EDF measures are derived from an empirical mapping of the historical average default rate consistent with each DD level.

Exhibit 3 compares the relationship between DD and PD for the basic BSM model (light blue line) and Moody's Analytics' public firm EDF model (dark blue line). Relative to the DD-EDF curve, the PDs derived from the BSM model vastly understate the true risk of default. For example, a firm with a DD of 4 has a probability of default that, for all intents and purposes, is zero under the BSM model (0.003%, to be exact). However, the EDF associated with a DD of 4 is 0.4%, 133 times higher than the Black-Scholes-Merton PD. As more than 90% of firms have DDs exceeding a value of 1 at any given time, the BSM model tends to understate default risk for the majority of firms.

Exhibit 3: EDF vs. BSM Probabilities of Default



2.2 Economic Forecasts and Alternative Scenarios

Moody's Analytics' ECCA economic forecasting models are structural macroeconometric specifications that allow various aspects of the economy to evolve interdependently in a multivariate error-correction framework, where short-run deviations from the system's dynamic equilibrium are modeled together with the long-run determinants of growth. In the broadest terms, the model system is specified to reflect the interaction between aggregate demand and supply. In the short run, fluctuations in economic activity are primarily determined by shifts in aggregate demand, including personal consumption, gross private investment, net exports, and government expenditures. The levels of resources and technology available for production are taken as given. Prices and wages adjust slowly to equate aggregate demand and supply. In the longer term, changes in aggregate supply determine the economy's growth potential, which is a function principally of the rate of expansion in the economy's resource and technology base.[13]

This modeling system is used to construct baseline forecasts and alternative scenarios, separately, for each country. Care is taken to ensure that the scenarios are internally consistent in that they satisfy the principles of macroeconomic theory. Rising GDP growth, for instance, is accompanied or followed by a declining unemployment rate, rising inflationary pressures and interest rates, and faster asset price growth. Changing one factor in a given scenario without solving the full structural model will jeopardize both the internal consistency of the economic scenario and the validity of the resulting Stressed EDFs.

The scenario forecasts can be viewed in the context of a distribution of economic outcomes that are consistent with a particular narrative of risks facing the economy. The baseline forecast represents ECCA's prediction of the most likely outcome given current conditions. The alternative scenarios are first sketched out around a simulation-based probability distribution of economic outcomes and then filled in formally through the ECCA macroeconomic model framework. These scenarios are cyclical—that is, they extend only through the current business cycle, with no change in the economy's long-run growth rate. Given the emphasis in stress testing on the downside, the Stressed EDF methodology employs three economic scenarios involving weaker than expected growth in addition to one scenario describing better than anticipated conditions.

[13] A more detailed description of the macroeconomic modeling approach used can be found in Zandi (2011).

Exhibit 4: Economic Scenario Descriptions[14]

Scenario	Description	Probability of Worse Outcome
S0	Baseline	50%
S1	Stronger near-term rebound	90%
S2	Slower near-term growth	25%
S3	Double-dip recession	10%
S4	Protracted slump	4%

Exhibits 5 through 15 illustrate the stressed dynamics of the US macroeconomic variables employed in the Stressed EDF models.[15]

Exhibit 5: US Real GDP, YoY change

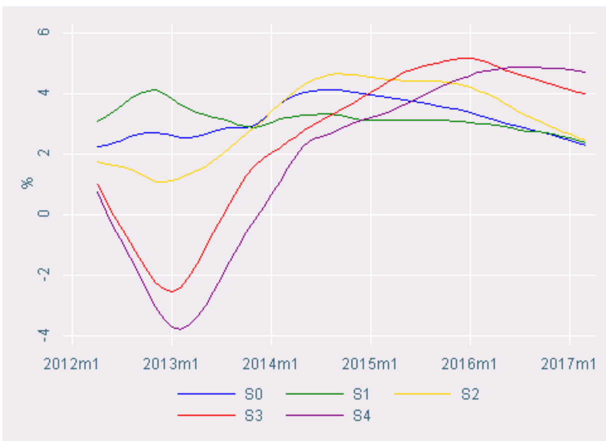


Exhibit 6: US Retail Sales, YoY change

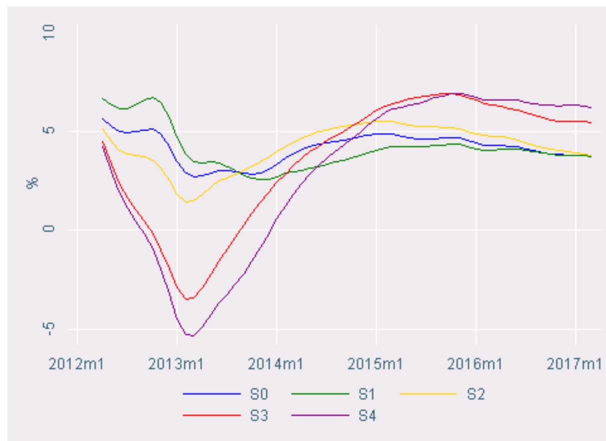


Exhibit 7: US Consumer Price Index, YoY change

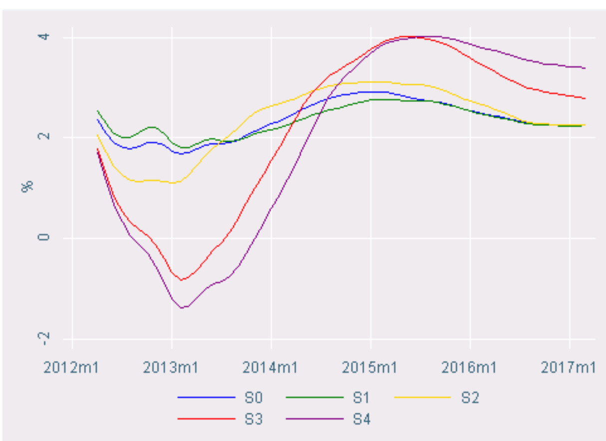
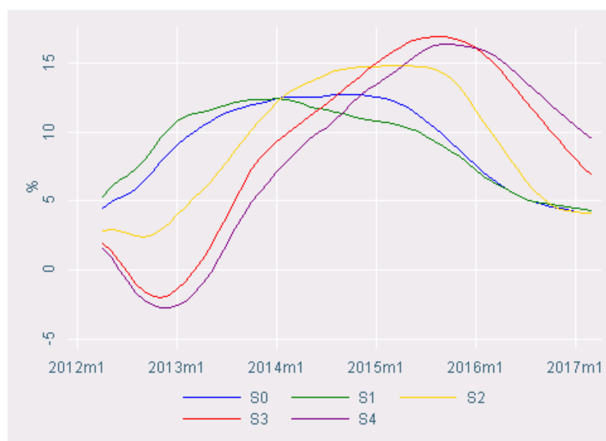


Exhibit 8: US Real Exports, YoY change



[14] The scenario descriptions and probabilities may change over time. Those described here are as of the April 2012 forecast cycle.
[15] As of April 2012.

Exhibit 9: US Unemployment Rate, YoY change

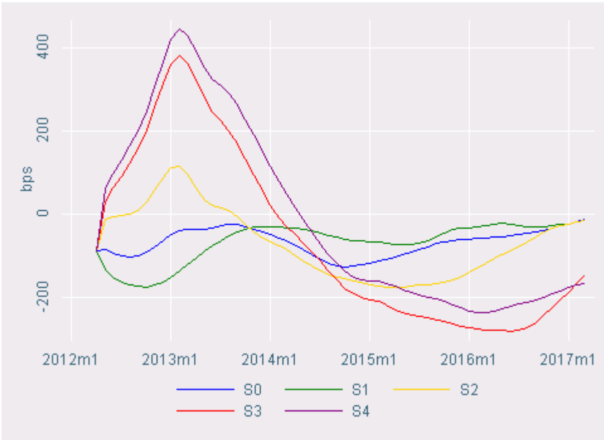


Exhibit 10: US Producer Price Index, YoY change

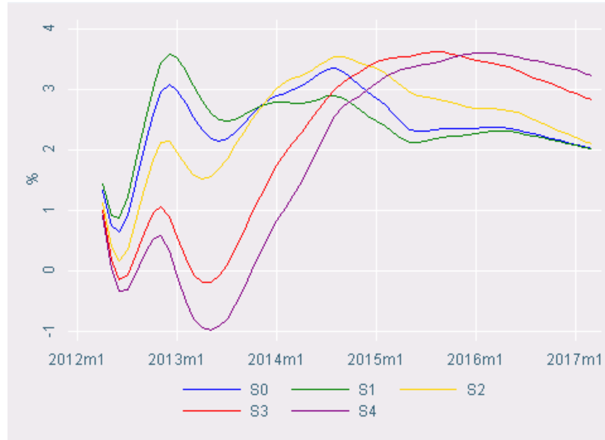


Exhibit 11: US Corporate Profits, YoY change

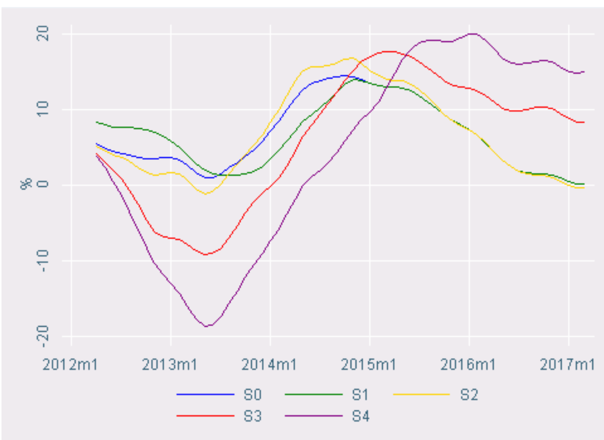


Exhibit 12: US Yield Curve[16]

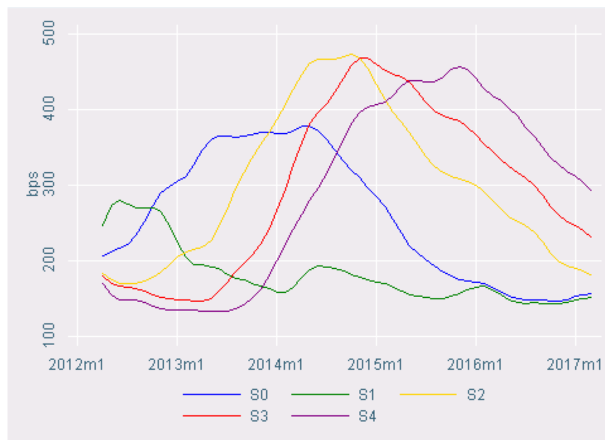


Exhibit 13: Ted Spread[17], YoY change

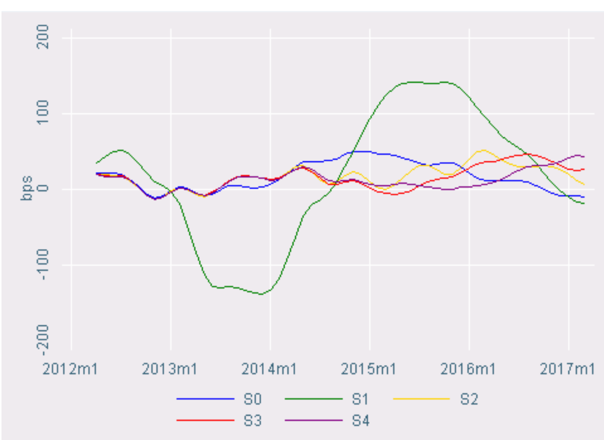
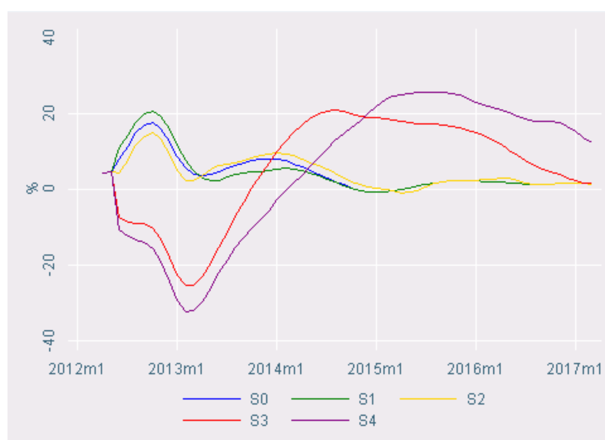
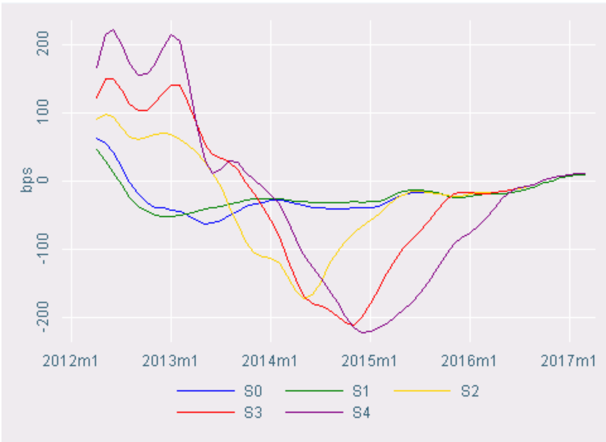


Exhibit 14: S&P 500 Index, YoY change



[16] The yield curve is defined as the difference between long- and short-term government bond rates.
[17] The Ted spread is defined as 3-month LIBOR less the 3-month US Treasury bill rate.

Exhibit 15: Baa Spread to US Treasury, YoY change



3 Stressed EDF Model Methodology

A key assumption of the Stressed EDF methodology is that credit risk at the firm level and in the aggregate exhibits procyclicality. PDs rise and fall, not as a result of ex post realizations of risk given a fixed PD distribution, but rather as a consequence of ex ante changes in risk that cause the entire distribution to shift over the cycle. Exhibit 16 shows a clear correspondence between aggregate credit risk and the business cycle – the median EDF for North American firms is relatively high during recessions and relatively low during economic expansions. Exhibit 17 shows the distributions of EDF measures in the expansionary and contractionary phases for the two most recent US business cycles. As shown in these box-plots, the distribution of EDF measures shifts to the right (i.e., higher PD) and the right-hand tail thickens during periods of economic stress.

Exhibit 16: EDF Median for North American Firms, 1979-2011

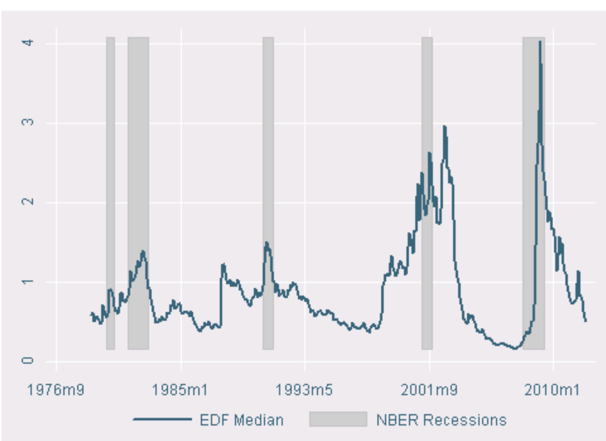
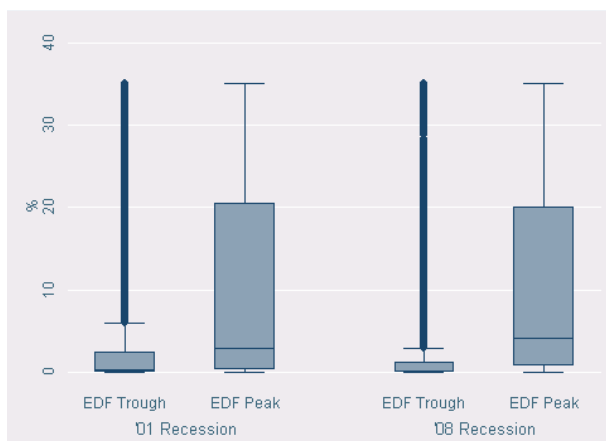


Exhibit 17: Box-Plot of EDF Distribution for North American Firms[18]



This should come as no surprise given that macroeconomic forecasts are implicit in the EDF measure.[19] Firms' asset values, for example, are derived from equity market prices. Asset values therefore reflect the market's view of the net present value of all future cash flows that will accrue to share holders, a view that is impacted by expectations for the future state of the macroeconomy. This effect can be seen in the fact that stock indices fall (rise) following unexpectedly bad (good) economic data

[18] Cyclical troughs in EDF medians occurred in September 1997 and June 2007. Cyclical peaks in EDF medians occurred in September 2002 and February 2009.

[19] Allen and Saunders (2003) give an overview of allowances for cyclical effects in different credit risk models.

releases. Macroeconomic expectations are also embedded in the default point. A company's determination of its optimal debt load depends on interest rates and its expectations for revenue growth given economic prospects.

Two other assumptions drive the Stressed EDF methodology. First, firm-level sensitivities to the macro factors are not homogenous. The default risk of a firm operating primarily in the energy sector, for example, might decline in the face of an oil price shock, while the PD of a trucking firm would likely rise. Similarly, we expect that the default risk of higher credit quality firms will respond differently to varying economic conditions than that of speculative grade firms. Second, credit risk is a function of both systematic factors and idiosyncratic risk, and the latter cannot be ignored when modeling at the firm level.

We model distance-to-default (DD) rather than EDF itself or the individual drivers of EDF (asset value, default point, and asset volatility). Because DD and EDF are linked by a monotonic mapping, they capture the same credit-relevant information and provide the same rank ordering. However, from a modeling standpoint DD is easier to work with than the EDF measure itself. While EDF measures are bounded between 1 bp and 35%, DD is more or less continuous. Also, like EDF, DD synthesizes all the informational content of its constituent drivers, which allows us to side-step the difficulties arising from nonlinearities in Equation (1) of modeling the drivers themselves and the computational challenges of modeling three drivers interdependently.

The Stressed EDF model is composed of two sub-models. For any given economic scenario and each of 60 months into the future, a firm level model determines each entity's rank order in the overall distribution of DD, while an aggregate level model determines the shape of that distribution. These sub-models are discussed in more detail in the following sections.

3.1 Firm-Level Model

The firm level model recognizes that both idiosyncratic and systematic risk impact a firm's default probability. Using a linear dynamic panel framework, we model the annual change in DD as a function of macro factors, industry, credit quality, and lagged DD changes. Using fixed effects estimators eliminates omitted variable bias arising from unmeasured, firm-level idiosyncratic risk. Specifically, we estimate the following equation:[20]

$$\Delta DD_{it} = \alpha + \boldsymbol{D}\rho + \boldsymbol{M}\beta + \boldsymbol{IND}\gamma + IG\delta + e_{it} \qquad (2)$$

where *i* and *t* are panel (firm) and time subscripts, respectively.

M is a vector containing 11 time-varying macroeconomic variables entering into the equation separately as well as interacted with industry and investment grade classification. Thus, we allow the sensitivity of credit risk to the macro factors to vary by sector and by credit quality. The 11 macro drivers, shown in Exhibit 5 through 15 were selected with several objectives in mind. First, the factor set should be broad enough to capture differences in alternative scenarios that might yield similar assumptions about overall economic growth – permitting relatively nuanced "what-if" analyses – while also respecting the old adage that less is more.[21] Second, the factors should be indicators that are generally well-known to market participants. This makes the economic scenarios and their corresponding Stressed EDF scenarios highly intuitive and accessible to a wide audience. Third, the macro drivers should include both traditional economic variables as well as financial market variables that are likely to impact systematic credit stress but may not be reflected in the standard macro variables. And, finally, the factors should have a long enough history to allow estimation of the models over as many business cycles as possible.

Industry fixed effects are included in the vector, ***IND***. We use 16 relatively homogenous industries likely to respond to economic conditions in a similar fashion. *IG* is a dummy variable classifying firms as investment grade/non-investment grade according to their Through-the-Cycle EDF-implied ratings. The TTC EDF-implied rating is largely immune to fluctuations due to short-term changes in credit quality and is therefore more appropriate than the traditional EDF-implied rating when estimating the fundamental relationship between default probability and systematic risk.[22] ***D***, a vector containing the one- and 12-month lags in

[20] This model specification imposes a requirement that firms have at least two years of DD history in order to calculate Stressed EDF measures.

[21] For example, both a 10% oil shock and a 20% house price shock scenario might be consistent with 2% GDP contraction, but the narrative of the two scenarios will impact Exxon Mobile much differently than Hovnanian.

[22] To see this, consider a firm whose traditional EDF-implied rating is usually Baa3, but due to temporary elevated volatility in equity markets falls to Ba1 for four months before returning to Baa3 once market conditions settle. It is unlikely that the sensitivity

the dependent variable, reflects each firm's recent credit history, which in turn reflects the cumulative impact of all past idiosyncratic and systematic risk for that firm.

Exhibit 18: Distribution of Industry and Investment Grade Classifications, North America Firms[23]

Industry	Frequency	Investment Grade Share
All	100%	22.2%
Consumer Discretionary	3.7	17.8
Defense	0.8	31.5
Agriculture	9.3	11.0
Consumer Staples	5.6	34.4
Transportation	2.1	19.3
Financial Services	19.9	31.7
Media	1.3	26.5
Materials	4.4	23.0
Business Products	8.9	19.1
Capital Goods	4.8	15.6
IT	10.4	16.2
Consumer Services	3.4	25.0
Health Care	10.1	15.7
Energy	7.7	14.8
Utilities	4.6	39.2
Unassigned	3.0	25.3

We estimate Equation (2) over a fixed historical time period between 2001 and 2011. Although we do not report them here (due to the proprietary nature of the model), the regression coefficients are nearly all highly significant, and as expected we find that the sensitivity of the annual change in DD to the macro factors varies with industry and credit quality. After obtaining estimates of the model parameters, we derive each firm's rank order in the DD distribution by applying those parameters to the macro drivers under each economic scenario.

A firm's projected rank order may change over time, within scenario, but the larger movements occur across scenarios. To understand why, consider a stylized example. Under today's benign economic conditions firms A and B reside at the 50th percentile of the DD distribution. A makes women's clothing. B operates a network of health care facilities. Under an adverse economic scenario, A and B are unlikely to remain at identical positions in the distribution. Perhaps A, whose business is highly cyclically sensitive, falls to the 40th percentile (lower DD, implying higher risk), while B, whose business is relatively immune to economic downturn, moves up to the 55th percentile.

This re-shuffling of firms as the distribution of PD changes over the business cycle is desirable for robust macro stress testing, especially at the portfolio level. A well-diversified portfolio will surely include corporate credit from firms spanning a variety of industries. Suppose, for example, one assumes that under a stressed economic scenario all of the firms represented in a given portfolio will respond in an identical manner to a set of macro drivers, and the assumed sensitivities to the macro drivers are based on average sensitivities measured across a hypothetical portfolio that includes all outstanding loans in the general population. If the composition of the portfolio being analyzed is overweight loans in cyclically robust industries and underweight loans in cyclically sensitive industries, then the stress analysis will overestimate the increase in stressed PDs over the baseline.

---

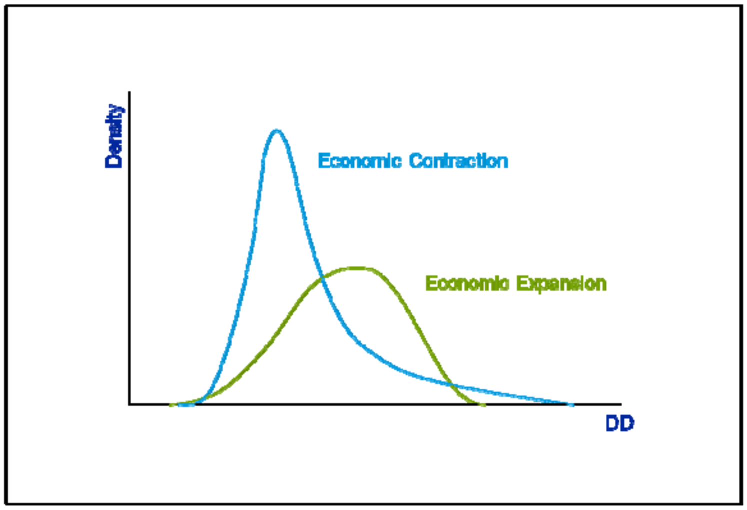
of this firm's credit risk to economic conditions changed fundamentally during those four months in which its traditional EDF-implied rating classified it as non-investment grade. Hamilton et al (2011) detail the methodology of TTC EDF measures.

[23] As of March 2012. Note that the sample consists of firms with EDF measures. Hence, the distribution of investment-grade and speculative-grade rated firms – which is based on TTC EDF measures – looks very different than what we observe for the population of firms with agency ratings.

3.2 Aggregate-Level Model

The aggregate-level model recognizes that the distribution of DD shifts under varying economic scenarios. In particular, the distribution shifts left (higher risk) and the right-hand tail thins and lengthens during economic downturns. The aggregate-level model is a pure macro model. That is, we model discrete segments of the DD distribution as a function of only the macro drivers.

Exhibit 19: Stylized Distributions of DD Under Good vs. Bad Economic Conditions



This results in estimation of the following 11 equations:

$$\ln\,(DD_t^{10} - DD_t^{01}) = \alpha + \boldsymbol{M}\beta + e_t \quad (3)$$
$$\ln\,(DD_t^{20} - DD_t^{10}) = \alpha + \boldsymbol{M}\beta + e_t \quad (4)$$
$$\ln\,(DD_t^{30} - DD_t^{20}) = \alpha + \boldsymbol{M}\beta + e_t \quad (5)$$
$$\ln\,(DD_t^{40} - DD_t^{30}) = \alpha + \boldsymbol{M}\beta + e_t \quad (6)$$
$$\ln\,(DD_t^{50} - DD_t^{40}) = \alpha + \boldsymbol{M}\beta + e_t \quad (7)$$
$$DD_t^{50} = \alpha + \boldsymbol{M}\beta + e_t \quad (8)$$
$$\ln\,(DD_t^{60} - DD_t^{50}) = \alpha + \boldsymbol{M}\beta + e_t \quad (9)$$
$$\ln\,(DD_t^{70} - DD_t^{60}) = \alpha + \boldsymbol{M}\beta + e_t \quad (10)$$
$$\ln\,(DD_t^{80} - DD_t^{70}) = \alpha + \boldsymbol{M}\beta + e_t \quad (11)$$
$$\ln\,(DD_t^{90} - DD_t^{80}) = \alpha + \boldsymbol{M}\beta + e_t \quad (12)$$
$$\ln\,(DD_t^{99} - DD_t^{90}) = \alpha + \boldsymbol{M}\beta + e_t \quad (13)$$

where t is a time subscript and DD^q represents DD at the qth quantile of the aggregate distribution.

We model DD at the median directly, but to ensure that the projected quantiles never cross, the dependent variables in equations (3)-(7) and (9)-(13) are defined as the natural log of the difference between contiguous quantiles. Projected DD at quantiles 1, 10, 20, 30, 40, 60, …, 90, and 99 are easily derived from these.

Although the inclusion of autoregressive terms would improve model fit, a key objective of Stressed EDF measures is the ability to properly assess credit risk under hypothetical adverse economic conditions. This requires that the model is appropriately sensitive to the macro factors. DD is highly autocorrelated, and the contribution to stressed PDs from the autoregressive terms would dwarf the contribution from the macro drivers resulting in only mildly stressed PDs even under a severely stressed economic scenario. We, therefore, estimate equations (3)-(13) as OLS regressions rather than as ARIMA(p,d,q) models, sacrificing some prediction accuracy on the baseline Stressed EDF forecast in the interest of the larger goal of using Stressed EDF measures for prudent stress testing.

As in the firm-level model, $\boldsymbol{M}$ is a vector containing the time-varying macro drivers, but the aggregate-level model equations employ a subset of the 11 used in the firm-level model, and those subsets vary by equation. The factor set for each equation was selected on the basis of two conditions. First, we required that the parameter estimates be statistically significant. Second, we required that the parameter estimates be of the expected sign.[24]

In the firm-level model, it is not always straightforward to assign a priori expectations for the signs on the macro variable coefficients, but in the aggregate it is possible to theorize that credit risk will respond in one direction or another to macroeconomic risk.[25] Growth in GDP, exports, retail sales, or corporate profits is likely to be positively correlated with DD since these indicators should improve earnings.[26] Conversely, a rising unemployment rate, which reflects weak growth, should have a negative impact on DD. Since asset value is derived from a firm's share price, growth in equity indices should be positively correlated with DD. DD should also rise with the yield curve, which reflects the market's expectations for long-term relative to short-term growth. Rising Baa and Ted spreads reflect increased financial market uncertainty and are likely to impact DD negatively, through asset volatility. Finally, in satisfying our conditions for variable inclusion, we require that inflation have a positive relationship to DD, although it could be argued that given consumer price inflation, higher producer price inflation raises costs, reduces profits, and lowers DD.

Since firm-level data quality issues prior to the early 1990s are more or less smoothed at the aggregate level, we are able to estimate equations (3)-(13) beginning in 1979. However, the macroeconomic realizations during the 2008 recession are so outside the historical norm in our sample that they act like noise, reducing the measured sensitivity of DD to the economic drivers and compromising our goal of producing sufficiently stressed EDF measures under the most adverse economic scenario. Therefore, the estimation sample is truncated to exclude the 2008 recession.

We apply the estimated model parameters to the forecasted economic scenario data to obtain projections for DD at quantiles 1, 10, 20, ..., 90, 99 of the distribution under each scenario and for each time period. The remainder of the distribution is filled in using linear interpolation.

3.3 Bringing It All Together

The third-to-last step in the methodology is to bring together the results from each of the two sub-models. The chart in the upper right-hand corner of Exhibit 20 shows a stylized example of the cumulative distributions of DD under the S0 (baseline), S1 (upside), and S2 (downside) scenarios (for a single point in time) that might be produced from the aggregate-level model. For a given time period and scenario, the firm-level model produces for each entity a projected rank ordering in the overall DD distribution that can be mapped to a position in the projected distribution arising from the aggregate-level model. This yields a stressed DD and is shown as step A in Exhibit 20. The unadjusted Stressed EDF metric is then obtained using our proprietary DD-to-EDF mapping system (step B).

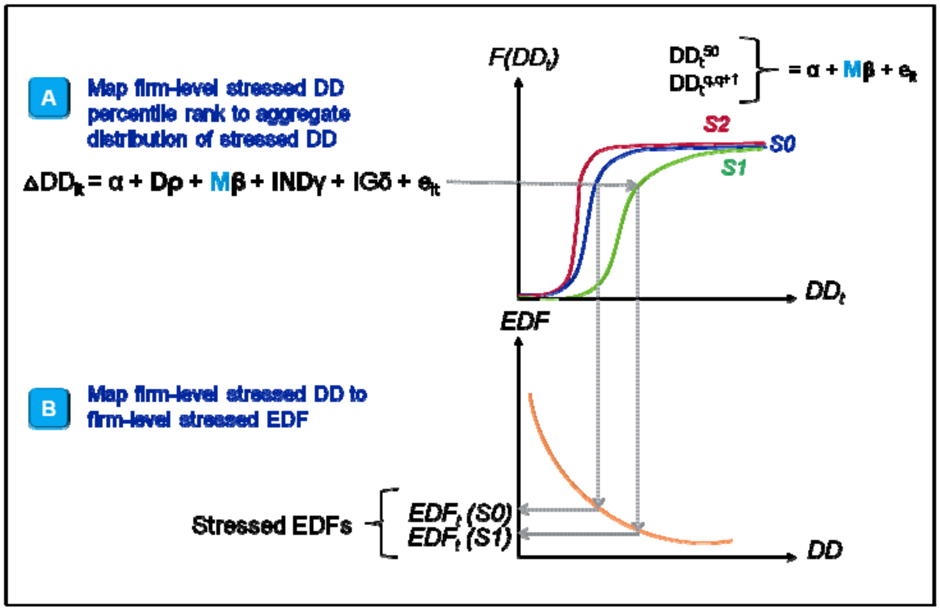
---

[24] Aside from lending legitimacy to the methodology, this ensures that the Stressed EDF scenarios will have the proper rank ordering in the aggregate. That is, that the Stressed EDF median under the least downside scenario is higher than in the baseline, the Stressed EDF median under the mid-severity downside scenario is higher than in the least downside scenario, and so on.

[25] Our findings are consistent with those of other studies. See, for example: Alves (2005); Bonfim (2006); Hamerle et al (2004); and Jimenez and Saurina (2006).

[26] GDP is the exception to rule #2, above, as it is included, contemporaneously, in all 11 specifications and always has a negative sign. GDP is always highly significant and its inclusion reduces mean squared error.

Exhibit 20: Stressed EDF Methodology In a Nutshell



In the final step of the model, we calibrate each firm's unadjusted Stressed EDF measures to reflect recent forecast errors. If, for a given firm, the model has been over- or underestimating default risk in recent months, the calibration will correct for that going forward. Specifically, we calculate the forecast error as the deviation between realized and forecasted EDF values. We then assume that the average of the most recent three months of forecast errors will persist into the future and calibrate the unadjusted Stressed EDF measures up or down accordingly.

4 Stressed EDF Model Validation

Stressed EDF measures are *conditional* forecasts, not forecasts per se. That is, they represent expected default probabilities given that the economic scenario on which they are based actually manifests. Therefore, Stressed EDF measures cannot be validated in the usual way. When validating unconditional forecasts, the typical practice is to compare out-of-sample forecasts with known realizations of the variable being forecasted. This procedure is not applicable to Stressed EDF measures, except in the extremely unlikely event that the macro drivers evolve in exactly the fashion described by the economic scenario. In other words, the performance of Stressed EDF measures relative to reality is dependent on not only the methodology but also the accuracy of the economic forecast scenarios. Although the baseline economic forecast is ECCA's estimate for the most likely outcome, it is still a forecast subject to error, and the alternative scenarios are just that – hypothetical alternatives that are not expected with great probability.

4.1 Defining a New Paradigm

It *is* possible to test the Stressed EDF methodology, but while the procedures follow the usual formula, the criteria for successful validation do not. As noted previously, to be useful in stress testing, Stressed EDF measures under the adverse economic scenarios must appropriately reflect the assumed degree of stress. But baseline Stressed EDF measures are also important. They may be used as stand-alone (conditional) PD forecasts, combined with Stressed EDF measures from alternative scenarios to produce weighted average, or expected value forecasts, or as the benchmark against which to compare Stressed EDF measures under the upside/downside scenarios.

The dual objectives of Stressed EDF measures – producing reliable (conditional) forecasts under both baseline and stressed economic conditions – change the loss function. A traditional forecasting model should seek to minimize the squared loss in Equation 14:

$$E(y_{t+i} - \hat{y}_{t+i})^2 \tag{14}$$

where $\hat{y}_{t+i}$ is the predicted value of y_{t+i} at time *t* and *i* is the stated forecast horizon.

In the case of stress testing, on the other hand, the loss function looks more like this:

$$\lambda[E_\Theta(y_{t+i} - \check{y}_{t+i})^2] + (1-\lambda)[E_\Psi(y_{t+i} - \tilde{y}_{t+i})^2] \tag{15}$$

where $\check{y}_{t+i}$ is the predicted value of y_{t+i} given the stressed event, Θ, occurs, $E_\Theta(\cdot)$ is the expectation given that the stressed event occurs, $\tilde{y}_{t+i}$ is the predicted value of y_{t+i} given the baseline event, Ψ, occurs, and $E_\Psi(\cdot)$ is the expectation conditional on the baseline event occurring.[27]

The mean squared errors (MSEs) shown in Exhibit 21 reflect the tradeoff between optimizing for the baseline scenario and optimizing for the stressed scenarios. Following the usual procedure, we estimated equations (2)-(13) on truncated samples and calculated out-of-sample MSEs from our preferred model specifications.[28] We compare these to the MSEs from a standard benchmark, the AR(1) model, for the same out-of-sample period. The firm-level model, which determines each entity's rank order in the aggregate distribution, performs better than the simple AR(1) model. The equations that determine the shape of the overall distribution, however, underperform the benchmark models. If the only objective were to produce a baseline PD forecast, it would be desirable for all of the preferred models to outperform the benchmark models. However, we feel that the Stressed EDF methodology appropriately balances the objectives of producing reliable and useful (conditional) forecasts under both baseline and stressed economic scenarios.

Exhibit 21: Mean Squared Error in Preferred vs. Benchmark Models

Equation	Dependent Variable	MSE - Preferred Model	MSE - AR(1) Model
2	ΔDD_{it}	0.291	0.302
3	$\ln(DD_t^{10} - DD_t^{01})$	0.092	0.005
4	$\ln(DD_t^{20} - DD_t^{10})$	0.129	0.005
5	$\ln(DD_t^{30} - DD_t^{20})$	0.070	0.003
6	$\ln(DD_t^{40} - DD_t^{30})$	0.046	0.003
7	$\ln(DD_t^{50} - DD_t^{40})$	0.050	0.001
8	DD_t^{50}	1.401	0.041
9	$\ln(DD_t^{60} - DD_t^{50})$	0.030	0.002
10	$\ln(DD_t^{70} - DD_t^{60})$	0.026	0.002
11	$\ln(DD_t^{80} - DD_t^{70})$	0.031	0.001
12	$\ln(DD_t^{90} - DD_t^{80})$	0.026	0.001
13	$\ln(DD_t^{99} - DD_t^{90})$	0.136	0.001

4.2 Perfect Foresight Exercise

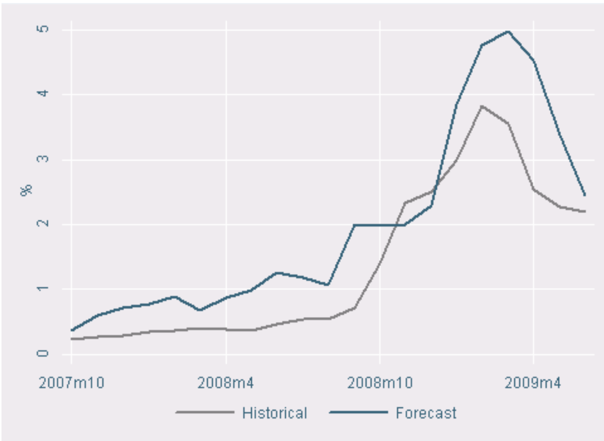
Since the economic contraction under the S4 scenario is currently designed to be as severe as in the 2008 recession, EDF peaks during that period can be used as a benchmark against which to compare Stressed EDF peaks under the S4 scenario. However, we can validate the Stressed EDF model methodology more formally using a "perfect foresight" test, as follows: First, we estimate the firm-level and aggregate-level models using only the information known through September 2007, before the onset of the financial crisis. Forecast error in the Stressed EDF metrics arises from model misspecification and deviations in the economic scenarios from realized economic data. To perform a pure test of the methodology, it is necessary to treat the true economic data

[27] For a more thorough discussion, see Hughes (2012).

[28] For these purposes, Equation (2) is estimated through September 2010, one year earlier than in the actual methodology. For reasons described in Section 3.2, the estimation samples for equations (3)-(13) already end before the present, so it is not necessary to further truncate the sample for this exercise.

since the fall of 2007 as a future, adverse economic scenario we might have considered at that time. We then calculate the corresponding Stressed EDF measures and compare them to actual EDF levels leading up to and during the crisis.

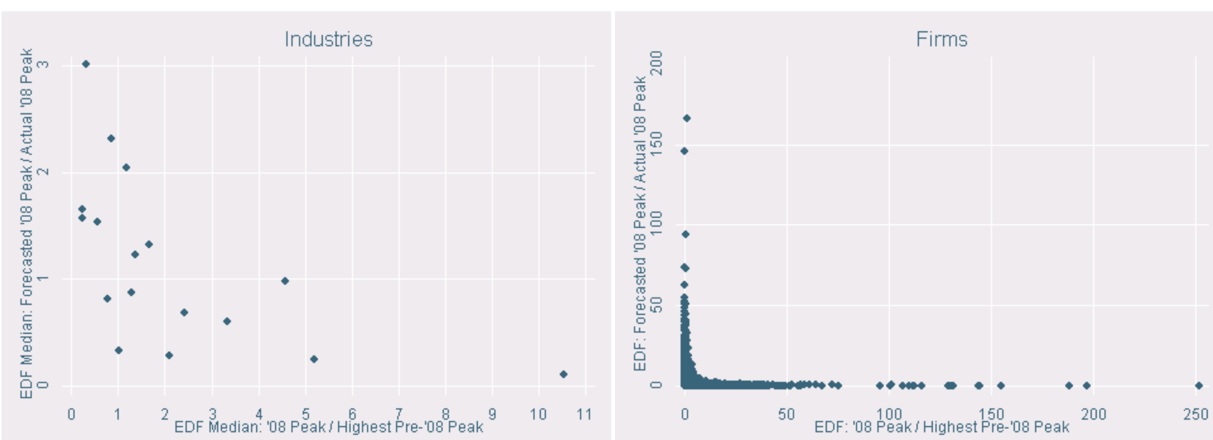
Exhibit 22: Actual EDF Median vs. Validation Exercise Stressed EDF Median, North American Firms



As shown in Exhibit 22, the perfect foresight validation exercise Stressed EDF median accurately predicts the timing of the peak in the actual EDF median for all North America firms. Prior to the crisis and at its apex, they are somewhat conservative relative to actual EDF measures. However, we view this as preferable to underestimating default risk when the cycle is turning from expansion to contraction.

Exhibit 23 reveals both the importance of sector-specific macro sensitivities and the benefit of having the experience of the 2008 recession embedded in the operational Stressed EDF methodology. Among industries and firms for which the 2008 recession EDF peak was extraordinarily high by historical standards (represented by the area to the right of one on the x-axis), the validation Stressed EDF peak underestimated the actual EDF peak (represented by the area below one on the y-axis).[29] Put another way, had the model been built in September 2007 – without the sector-specific extraordinary experience of the 2008 recession in its estimation period – it would have been unable to predict the degree of stress in PDs that occurred among especially hard-hit industries such as financials and consumer discretionary. Fortunately, the current Stressed EDF model has the benefit of hindsight that includes the most severe financial crisis since the Great Depression.

Exhibit 23: Historical EDF Peaks vs. Validation Exercise Stressed EDF Peaks, North American Firms



[29] Also, among industries and firms for which past EDF peaks exceeded the 2008 recession peak (represented by the area to the left of one on the x-axis), the validation Stressed EDF peak overestimated the actual EDF peak (represented by the area above one on the y-axis).

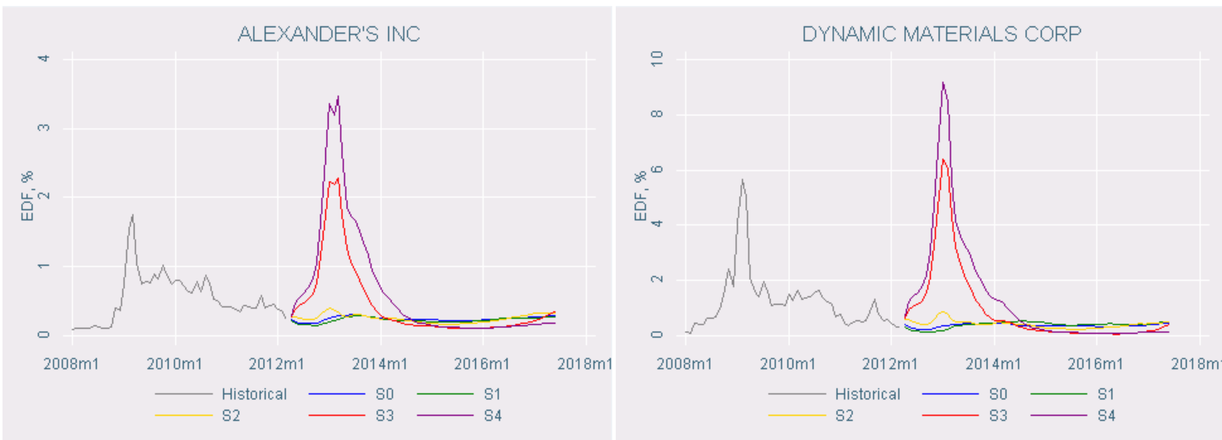
5 Examples and Applications

In this section we demonstrate some potential applications of Stressed EDF measures with a few examples. Stressed EDF metrics can be used whenever a PD is required to assess credit risk in alternative, future states of the world.

5.1 Single-Name Credit Risk Management

Consider a portfolio manager presented with the opportunity to buy two bonds which are both priced at par.[30] The latest EDF measures for the corresponding firms suggest that based on fundamental analysis, their one-year default risk is nearly identical. In Exhibit 24, below, Alexander's, Inc. and Dynamic Materials, Corp. have PDs of 0.35% and 0.31% in February 2012.[31] The portfolio manager would be indifferent between these two bonds were it not for an investment directive requiring that the portfolio be optimized for minimal volatility during periods of financial stress. Furthermore, the fund employs a buy-and-hold investment strategy with an investment horizon of three years.

Exhibit 24: Stressed EDF Credit Measure Examples



In this situation, the Stressed EDF paths could be used to inform the asset selection decision. Although the current EDF measures for the two firms show their one-year default risk to be quite comparable as of the latest data available, Stressed EDF measures suggest that the credit risk of Alexander's, Inc. is more robust to the hypothetical, adverse economic scenarios than is the default probability of Dynamic Materials, Corp. Under the S4 scenario, for example, Dynamic Materials, Corp.'s one-year Stressed EDF peak is nearly 3 times higher than Alexander's Inc.'s. This example shows that cross-firm comparisons of Stressed EDF measures under adverse economic scenarios could be an important criteria in asset selection when the investment objective includes minimizing credit vulnerability to economic downturns and/or financial stress.

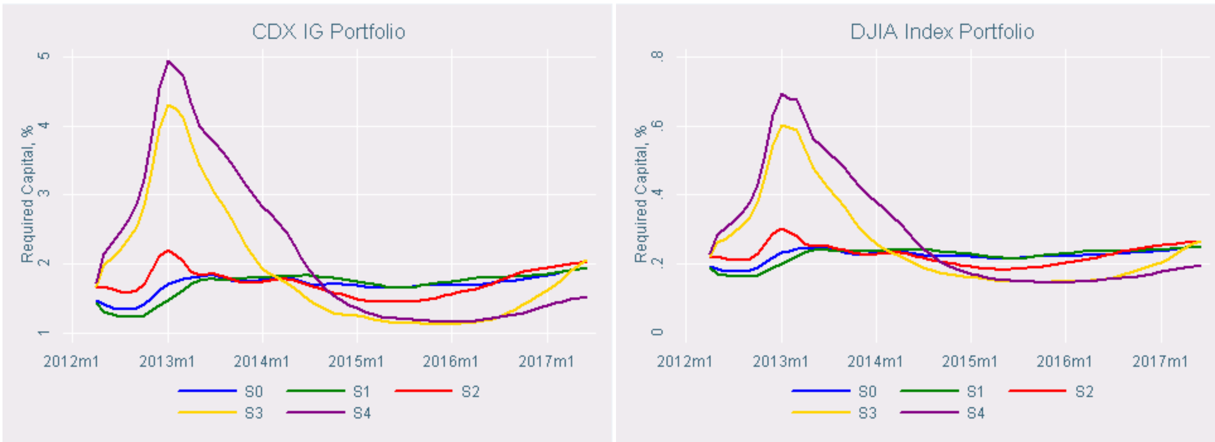
5.2 Portfolio Example: Calculating Regulatory Capital

In this example we show how Stressed EDF measures can be used to forecast regulatory capital requirements under hypothetical, stressed economic conditions. The Basel accords, for instance, advocate the need for incorporating economic assumptions in stress tests of capital adequacy, and Stressed EDF measures can help fulfill this need.

For this exercise we calculate Basel II/III required capital for two sample portfolios, the CDX North America Investment Grade (CDX IG) index and the Dow Jones Industrial Average (DJIA) stock index. The CDX IG is an equally weighted index of the 125 largest, most liquid investment-grade North American corporate reference entities. The DJIA stock index consists of 30 "blue chip" companies selected by the Wall Street Journal. Although other inputs, such as loss given default, may also be impacted by economic conditions, we simplify the exercise by varying only the PD input into the calculation.[32]

[30] This assumption is made for the sake of example and does not reflect actual or expected bond prices for the firms used in the exercise.
[31] EDF measures around 0.31%-0.35% correspond to ratings in the Baa range, historically, so these are low quality, investment-grade rated firms.
[32] For the calculations we assumed equal exposure sizes and a loss given default rate of 30%.

Exhibit 25: Basel II/III Required Capital Using Stressed EDF Measures



The stressed regulatory capital requirements for each portfolio are shown in Exhibit 25. Since the DJIA portfolio is comprised of relatively high credit quality firms with long histories of operating profitability, all of the projected required capital paths lie below those of the CDX IG portfolio. But, several stylized facts are common to both portfolios. First, capital requirements are relatively stable when calculated using the baseline PD, which is consistent with a relatively stable economic outlook in the baseline scenario. Second, capital requirements rise significantly when based on the PDs derived from the two most adverse economic scenarios. Under the S4 scenario, required capital rises by more than a factor of three in both portfolios.

Although this analysis could be done with portfolio-level assumptions for PDs conditioned on stressed economic conditions, we believe that the bottoms-up approach proffered by Stressed EDF measures provides an improvement in accuracy that should not be discounted, particularly in matters of capital adequacy. Since Stressed EDF measures are available at the firm level and they incorporate assumptions about industry and entity-level heterogeneity, aggregation within a portfolio context will explicitly account for portfolio composition. In the CDX-IG portfolio, for example, it would be unrealistic to assume that the PD of all 125 firms would respond in a similar fashion to a given stressed economic scenario. It would be difficult to tailor any portfolio-level assumptions to the specific composition of the portfolio. At best, one might employ industry-specific assumptions and combine these with the industry distribution of the portfolio's constituents, but even that would ignore important differences in default probabilities arising from firm-level idiosyncratic risk.

Furthermore, bottoms-up portfolio analytics using Stressed EDF measures have a direct connection to the underlying macroeconomic scenarios. That is, economic or regulatory capital figures derived from Stressed EDF measures can be easily intuited if one is familiar with the macroeconomic scenarios. Thus, basic sensibility checks are possible by even those with only a cursory understanding of the quantitative models behind the economic or regulatory capital estimates.

5.3 Setting Credit Limits

Many banks and insurance companies have committees that set credit limits for lending and investment activity in particular industries or geographic regions. This section describes how existing credit limits might be augmented using Stressed EDF measures. In this example, we calculate the ratio of S4 to S0 Stressed EDF measures one year into the future and show the mean and median of these ratios, by sector, in Exhibit 26. We also rank order each sector based on these metrics.

Exhibit 26: An Industry-Level Robustness Measure for North America Firms

Industry	Mean of S4/S0 Stressed EDF	Mean-Based Rank	Median of S4/S0 Stressed EDF	Median-Based Rank
Consumer Discretionary	24.2	14	4.23	10
Defense	6.9	3	5.30	13
Agriculture	29.6	15	3.64	3
Consumer Staples	12.3	6	3.92	9
Transportation	4.5	1	3.85	6
Financial Services	5.5	2	2.73	2
Media	14.6	8	4.48	11
Materials	15.9	10	6.56	15
Business Products	7.8	4	3.90	8
Capital Goods	12.9	7	3.84	5
IT	21.2	12	3.75	4
Consumer Services	14.8	9	5.07	12
Health Care	9.7	5	2.66	1
Energy	23.3	13	3.86	7
Utilities	16.2	11	5.37	14

The S4/S0 ratios and their associated ranks describe each industry's relative robustness to a severe economic climate one year down the road. For instance, the Stressed EDF model suggests that given a hypothetical, very adverse economic scenario, firms in the consumer discretionary industry would, on average, have PDs in April 2013 more than 24 times higher than in the baseline scenario. Unsurprisingly, this ranks the consumer discretionary industry near the bottom among the 15 industries shown.

This simple robustness measure could be used as an additional input into the process of setting industry-level concentration limits for lending or investment portfolios or as a tool for benchmarking that process. Additionally, it might be desirable to set name-level restrictions for entities whose one-year ahead S4/S0 Stressed EDF ratio exceeds its industry's mean or median. An additional layer of credit risk management such as this is useful when it is not possible to fully avoid a relatively high credit risk industry or geographic region.

6 Stressed EDF Measures Based on User-Defined Macroeconomic Scenarios

The "off-the-shelf" Stressed EDF measures that Moody's Analytics calculates and publishes on a monthly basis are derived from ECCA's S0-S4 macroeconomic scenarios as well as key regulatory-driven scenarios, such as the Fed's supervisory baseline and stress scenarios and (in the future) the EBA's stress testing scenarios. However, there is a need for stressed PDs conditioned on user-defined macroeconomic scenarios, arising either from regulatory requirements or an internally-driven desire to impose consistency throughout an organization's economic input assumptions. The Federal Reserve's annual stress testing exercise, for example, requires each participating bank to estimate losses, revenues, expenses, and capital ratios under its own baseline and stressed economic scenarios in addition to the Fed's scenarios. Banks under the aegis of regulators other than the Fed or EBA, such as those in the UK or Switzerland, will likely find value in "custom" Stressed EDF metrics derived from the stress testing requirements of their own particular regulators.

The CreditEdge platform allows users to generate Stressed EDF measures based on a custom specified economic scenario. First, users download a blank economic scenario template (an Excel frame) listing the date/country/variable combinations employed by the Stressed EDF model. Second, users fill in the template with their own economic forecasts. Third, users upload the completed template to CreditEdge. Users are notified by email that the scenario submission has been received for processing, and are emailed again when the custom scenario-based Stressed EDF metrics are ready for retrieval. The latter email includes a URL from which the custom Stressed EDF measures can be retrieved.

It is necessary only that the user specify economic scenario forecasts for at least one macroeconomic variable in the custom scenario data template. This accommodates the likely possibility that users do not have forecasts for all of the variables (across all countries) employed by the Stressed EDF model specifications. The custom Stressed EDF model completes a partially filled template using an algorithm developed by ECCA that also ensures that the macroeconomic time series are mutually consistent. For example, if a user specifies forecasts for US GDP growth, unemployment, and consumer inflation, the algorithm will calculate forecasts for US consumption, investment, exports, retail sales, etc. (as well as forecasts for all other countries) that are internally consistent from a macroeconomic modeling standpoint with the user's forecasts.

The multi-country "custom scenario generator" algorithm and its benefits and limitations are discussed in detail in Hanson, Hughes, and Kanigel (forthcoming), but is summarized in brief here. The algorithm makes use of ECCA's BL and S1-S4 economic scenarios that are updated monthly and two "bookend" scenarios, also updated monthly. The bookend scenarios represent the outer ranges of highly unlikely but still plausible economic outcomes. Both the upside and downside bookend scenarios are viewed as 1-in-10,000 probability events. The scenario generating process is best described using an example. Suppose a user provides inputs (forecasts) for German GDP growth and US CPI inflation. The algorithm uses the differences between the user-provided input paths and ECCA's baseline scenario paths for those variables to simulate input paths of GDP growth in all countries but Germany and of CPI inflation in all countries but the US. Then, for each country and each time period in the forecast horizon, the algorithm computes an index made up of the actual and simulated inputs for GDP growth and CPI inflation and minimizes the distance between this index and an analogous index made up of the "off-the-shelf" scenarios. The time-varying weights for the BL, S1-S4 and bookend scenarios that solve this optimization problem are then used to calculate forecasts for all other variables. The index of actual and simulated inputs weights each variable equally. This has practical implications only when the economic relationships between the user's inputs are inconsistent with those in the Moody's Analytics' structural macroeconomic model.

7 Conclusion

In this paper we describe the modeling methodology behind Moody's Analytics Stressed EDF measures. Stressed EDF measures are one-year, default probabilities conditioned on holistic economic scenarios developed in a large-scale, structural macroeconometric model framework. This approach has several advantages over other methods, especially in the context of stress testing. Stress tests or scenario analyses based on macroeconomic drivers lend themselves to highly intuitive interpretation accessible to wide audiences – investors, economists, regulators, the general public, to name a few. Even more powerful are stress tests based on economic scenarios built around specific, plausible narratives that reflect current conditions, structural relationships among different sectors of the economy, and a layer of human expertise.

Stressed EDF measures are therefore well-suited to applications in which PDs conditioned on future, alternative states of the world are required. Their availability at the firm level provides added flexibility over aggregate-level PDs. Credit analysis can be done at the single-name level, as in our asset selection example of Section 5.1, or at the portfolio level, as in our Basel II/III required capital example of Section 5.2. When assessing credit risk at the portfolio level, Stressed EDF measures allow one to account for portfolio composition, a difficult or impossible task when using aggregate-level PDs.

Possible uses for Stressed EDF measures are not limited to those discussed here, however, nor are they limited to stress testing. Although they are also conditional PDs, the baseline Stressed EDF measures are conditioned on Moody's Analytics' economic forecasting unit's most educated estimate for the likely evolution of the macroeconomy. The baseline PDs, or a weighted average of two or more Stressed EDF measures, would serve well whenever estimates for the most likely future path of PDs are required. In this vein of thought, one potential application that needs further exploration is using Stressed EDF measures for relative value bond analysis.

References

Allen, L., & Saunders, A. (2003). *A Survey of Cyclical Effects in Credit Risk Measurement Models.* BIS Working Paper No. 126.

Alves, I. (2005). *Sectoral Fragility: Factors and Dynamics.* BIS Papers No. 22.

Asberg, P., & Shahnazarian, H. (2008). *Macroeconomic Impact On Expected Default Frequency.* Sveriges Riksbank Working Paper No. 219.

Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy , 81*, 637-659.

Bonfim, D. (2006). *Credit Risk Drivers: Evaluating the Contribution of Firm-Level Information and of Macroeconomic Dynamics.* Bank of Portugal Economic Bulletin and Financial Stability Report Articles.

Boss, M. (2002). *A Macroeconomic Credit Risk Model for Stress Testing the Austrian Credit Portfolio.* Oesterreichische National Bank Financial Stability Report 4.

Breuer, T., & Krenn, G. (2000). *Identifying Stress Test Scenarios.* Fachhochschule Vorarlberg and Oesterreichische National Bank Working Paper.

Bunn, P., Cunningham, A., & Drehmann, M. (2005). *Stress Testing As A Tool For Assessing Systemic Risks.* Bank of England Financial Stability Review.

Chan-Lau, J. A. (2006). *Fundamentals-Based Estimation of Default Probabilities: A Survey.* IMF Working Paper No. 149.

Crosbie, P., & Bohn, J. (2003). *Modeling Default Risk.* Moody's Analytics Working Paper.

Drehmann, M. (2005). *A Market Based Macro Stress Test for the Corporate Credit Exposures of UK Banks.* Bank of England.

Dwyer, D., & Qu, S. (2007). *EDF 8.0 Model Enhancements.* Moody's Analytics White Paper.

Foglia, A. (2009). Stress Testing Credit Risk: A Survey of Authorities' Approaches. *International Journal of Central Banking , 5* (3), 9-45.

Hamerle, A., Liebig, T., & Scheule, H. (2004). *Forecasting Credit Portfolio Risk.* Deutsche Bundesbank Discussion Paper Series 2: Banking and Financial Supervision, No. 1.

Hamilton, D. T., Sun, Z., & Ding, M. (2011). *Throught-the-Cycle EDF Credit Measures.* Moody's Analytics White Paper.

Hughes, T. (2012). *Validating Stress Testing Models.* Moody's Analytics Economics and Consumer Credit Analytics Working Paper.

Hughes, T., & Liu, Z. (2011). *Stressing EDF Credit Measures Using Macroeconomic Scenarios.* Moody's Analytics White Paper.

Hughes, T., Licari, J. M., Mashayekhi, F., & Wang, J. (2007). *Stress Testing Corporate Credit Risk.* Moody's Economy.com Regional Financial Review.

Jacobson, T., Linde, J., & Roszbach, K. (2005). *Exploring Interactions Between Real Activity and the Financial Stance.* Sveriges Riksbank Working Paper No. 184.

Jimenez, G., & Saurina, J. (2006, June). Credit Cycles, Credit Risk, and Prudential Regulation. *International Journal of Central Banking* , 65-98.

Merton, R. C. (1973). Theory of Rational Optional Pricing. *Bell Journal of Economics , 4*, 141-183.

Pesaran, M. H., Shuermann, T., Treutler, B. J., & Weiner, S. M. (2005). *Macroeconomic Dynamics and Credit Risk: A Global Perspective.* Working Paper.

Virolainen, K. (2004). *Macro Stress Testing With a Macroeconomic Credit Risk Model for Finland.* Bank of Finland Discussion Paper 18.

Zandi, M. (2011). *The Moody's Analytics US Macroeconomic Model.* Moody's Analytics Economic and Consumer Credit Analytics.

Acknowledgements

The authors thank Zhou Liu, Xu Chen, and Juan Licari for laying the groundwork for this methodology and David T. Hamilton and Zhao Sun for valuable feedback and comments during development.

.